Feature and Classifier selection for Computer Assisted EEG Interpretation

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Abstract: Computer analysis of the routine EEG may assist in the visual interpretation to reduce inter- and intra-observer variability. In addition, it may improve the diagnostic yield of the EEG, if clinically relevant features can be extracted that cannot otherwise be perceived or quantified by human, visual, interpretation. Furthermore, it may save time in a (busy) clinical environment. Finally, computer analysis of the EEG is essential in long-term monitoring of brain function with continuous EEG (cEEG). We present results of the analysis of 819 routine EEG recordings from our own laboratory. Various features (p=87) were extracted from each EEG, that were subsequently evaluated in their differentiating capacity using several classifiers. Features included statistical descriptors, several spectral and synchronization measures and symmetry measures. Different classifiers were trained and evaluated using independent data sets, repeated a number of times (cross-validation). The final goal of the classification procedure was to differentiate between normal and abnormal EEG background patterns, using the visual interpretation of experts as the reference. Our results show sensitivities between 80-89% and specificities of 50-65%. Finally, we estimated ROC curves. This allows the setting of a particular sensitivity and specificity, that can be defined depending on the clinical context.

Introduction

EEG interpretation in clinical neuro(physio)logy is typically performed by visual analysis [1]. For several decades, various attempts have been performed to support the physiologist with computer assisted and (semi)automatic EEG interpretation. The motivation includes known inconsistencies in the visual interpretation due to inter- and intra-observer variation [1, 2], the rather long learning curve and efficiency. In addition, for clinical monitoring with continuous EEG, computer analysis with extraction of the relevant features is essential [3, 4, 5, 6, 7, 8]. Also, computer analysis may improve the diagnostic yield of the EEG, if clinically relevant features can be extracted that cannot be perceived or quantified by human, visual, interpretation.

However, at present, automatic EEG interpretation is still in its infancy, and the application in a clinical environment for the classification of routine EEG recordings is rather limited [9].

In this paper, we describe the results of the analysis of 819 EEGs, that was aimed to differentiate recordings with a normal background pattern from recordings with an abnormal background pattern. The EEG background pattern refers to the pattern that determines the average statistical features of the recording, and does not include transients, such as 'rhythmic discharges' and epileptiform abnormalities. This background pattern does, however, contain relevant clinical information about the state of the patient (awake, asleep, drowsy) and can be abnormal in many neurological conditions. Examples include patients who suffered from an intracerebral infarction or hemorrhage, particular forms of dementia and metabolic encephalopathies [10].

Materials and Methods

EEGs were recorded with a Brainlab digital EEG system (OSG, Belgium) using a 500 Hz sampling frequency (16 bit). Filter settings were 0.16-70 Hz. The EEGs were recorded with Ag/AgCl electrodes placed at the Fp2, Fp1, F8, F7, F4, F3, A2, A1, T4, T3, C4, C3, T6, T5, P4, P3, O2, O1, Fz, Cz and Pz loci of the international 10-20 system. Impedance was kept below 5 KΩ.

We used 819 EEGs, that were recorded in the period 2002-2003, at the department of clinical neurophysiology in HagaZiekenhuis, The Hague, Netherlands. Two sets of EEG were created. Set 1 contained raw, non pre-processed EEG data (n=577), with typical durations between 20 and 40 minutes. Set 2 contained 242 artefact free EEG epochs, including labeled epochs with eyes closed and eyes open. This set was obtained from different patients than set 1. However, both sets were recorded in the same department, and contained a comparable number and type of normal and abnormal EEGs. The total length of these artefact free epochs ranged from 1 to 3 minutes. The background pattern of all EEGs were labeled by experts. These labels were extracted from the digital database of the clinical neurophysiology department. The sets used are summarized in table 1.

Features

A total of 87 features were extracted from all EEG recordings, and included statistical features (mean, vari-

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Table 1: Percentages normal and abnormal EEGs of the two sets used. Normal and abnormal relate to the background pattern.

Set	**# EEGs**	**normal**	**abnormal**
Set 1	577	73.5%	26.5%
Set 2	242	68.8%	31.2 %

ance, kurtosis, skewness), spectral features, synchronization measures and features related to particular forms of symmetry. Due to space limitations, we only present a short overview in Table 2.

Table 2: Overview of some features used.

Feature	**Examples**	**refs**
Descriptive statistics	variance, kurtosis, skewness	[11]
Synchronization	phase sync. (Hilbert)	[12, 4]
Spectral	dominant alpha, reactivity	[10, 13]
Symmetry	BSI and variants	[4, 5]
Transients	sharp waves, peaks	[10, 13]

The particular choice of the features was partially motivated by insight into the strategies used in the visual analysis, e.g. the peak frequency of the α-rhythm over the occipital areas. In addition, measures for symmetry, such as the brain symmetry index [4, 5], bear a direct relationship with the strategy used in the visual interpretation. However, we also explored features that are more difficult if not often impossible, to appreciate by visual analysis, such as skewness, kurtosis, or (some forms of) synchronization.

Feature Selection and Classifiers

The goal of the classification procedure was to differentiate between normal and abnormal EEG background patterns, i.e. a two-class classification problem.

We apply the following methods to train various classifiers on the given datasets. Using prtools (www.prtools.org), the following classifiers were used: Lasso, Liknon, C4.5, K-NN , Nearest Saled Mean Classifier (NSMC), Quadratic Classifier (Quadrc), and a Neural Network Classifier (Neurc). Given the relatively large number of features extracted, reduction in the dimensionality of the problem may be necessary [14]. Traditionally this is done in an explicit feature selection preprocessing step. More advanced classifiers have an internal regularization mechanism for this purpose (Lasso and Liknon). Then, an additional regularization parameter allows for weighting data fit and model sparseness. In our experiments, this regularization parameter is optimized in an additional internal double 5-fold cross-validation loop. The parameter value for which the average of the sensitivity and specificity is minimal is considered optimal. For the classifiers that do not have an integrated dimension reduction mechanism (K-NN, NSMC, Quadrc and Neurc), we use Sequential Forward Selection (SFS) with the nearest neighbor criterion. Further, the confidence parameter for C4.5 and the number of neighbors for K-NN are tuned as the regularization parameters with a double 5-fold cross-validation loop.

Performance Estimation

For the classification of the EEGs using the proposed feature set, we apply several classifiers, as discussed previously. As a measure for the performance we estimate the sensitivity and specificity with a four times repeated 10-fold cross-validation protocol. The sensitivity is computed as the average number of correctly classified normal background patterns and the specificity as the average number of correctly classified abnormal background patterns, i.e.

$$\text{sensitivity} = P(T+|D+) \tag{1}$$

and

$$\text{specificity} = P(T-|D-), \tag{2}$$

with $D+$ the presence of a normal background pattern, $D-$ the absence of a normal background pattern, $T+$ a normal background pattern defined by computer analysis and $T-$ the absence of a normal background pattern obtained from computer analysis, respectively.

Results

An overview of the performance of the different classifiers, using the sensitivity and the specificity as relevant measures, is presented in Tables 3 and 4 for the two different EEG sets, set1 and set2, respectively.

Table 3: Overview of 7 classifiers used to differentiate normal from abnormal EEG background patterns, data set 1 (n=577 EEGs).

Classifier	**Sens %**	**Spec %**
Lasso	91.8±3.7	53.9±13.9
Liknon	93.4±3.6	51±12.6
C4.5	85.3±5.0	52.1±11.2
K-NN	85.2±5.7	52.4±13.0
NMSC	82.9±5.1	65.9±12.0
Quadrc	96.6±3.7	34.8±12.5
Neurc	87.9±5.1	52.4±12.5
Average	89±4.7	51.8±4.5

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Table 4: Results of the analysis of pre-processed, artefact free EEGs (Set 2, n=242).

Classifier	**Sens %**	**Spec %**
Lasso	91.8±7.0	60.5±13.9
Liknon	90.3±8.1	68.3±17.4
C4.5	87.4±7.3	65.8±16.7
K-NN	82.8±8.3	60.5±17.4
NMSC	85.7±8.4	71.2±17.6
Quadrc	81.6±10.2	65.0±19.4
Neurc	86.0±7.2	61.7±16.8
Average	86.4±4.9	64.7±5.2

The average sensitivity in set 1 and set 2 is about 87%. The specificity in set 1 is approximately 52%. Preprocessing of the data (set 2) improves the specificity by about 13%. The number of features selected ranged from 33±8.7 (C4.5) to 65.9±7.9 (SFS) in set 1, with an average of ∼50, while in set 2 (artefact free), the number of features selected was 9.8±3.9 in the SFS to 18.8±9.3 in the Liknon, with an average of ∼ 14.

Using set 2, we also constructed ROC curves, for different numbers of features used. An example is presented in Figure 1. In this case, the learn set consisted of 95% of the 242 EEGs, the test set of the remainder. This procedure was repeated 20 times, using a quadratic classifier.

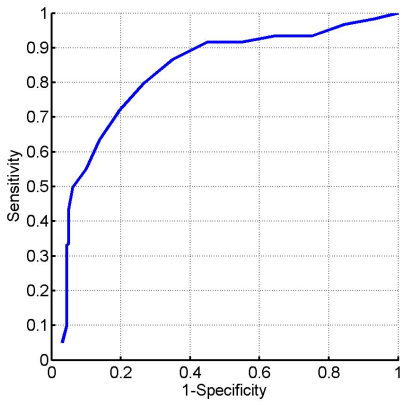

Figure 1: ROC curve of set 2, showing the sensitivity as a function of (1-specificity) for 8 selected features and a quadratic classifier. The most relevant features related to the occipital peak frequency, and to the anterior-posterior and left-right spectral symmetry (BSI).

Discussion and Conclusion

The current study evaluates the performance of different classifiers and features in their ability to differentiate between normal and abnormal EEG background patterns. Although the concept of 'background pattern' is ill-defined (see e.g. [10]), in the current context it is regarded as the EEG pattern that determines the average statistical features of the recording, and therefore does not include transients, such as peaks and sharp waves.

More than 800 EEG recordings were used, all labeled by experts. The labels were obtained from the digital EEG data base. A part of the EEG set contained artifact free data, obtained after visual pre-processing of the data (set 2).

Our analysis shows that the average sensitivity obtained in set 1 and set 2 is about 87%. The specificity in set 1 is approximately 52%, and improves in set 2, after artefact rejection, to ∼ 65%. The number of features selected was significantly lower in the artefact free EEG group (set 2), with a value of ∼14 than in the 'raw' EEG data set (∼50). Therefore, artefact rejection seems to both improve the performance of the classifier, and reduces the number of selected features. We could not find a particular classifier that significantly outperformed any other classifier, using the sensitivity and specificity as performance measures.

In addition, we constructed ROC curves for set 2, using different numbers of features. An example is shown in Figure 1, where 8 features were selected. Construction of ROC curves allows the setting of a particular sensitivity and specificity, that can be defined depending on the clinical context.

The most relevant features found were related to the dominant frequency over the posterior areas and measures for symmetry. Insight into the most relevant features may e.g. assist in further optimizing the sensitivity and specificity of these features, and provide additional insight into the strategies used by human visual interpretation.

The current performance is not sufficient for clinical application, that would need a sensitivity of $> 98\%$ and specificity of $> 98\%$. This implies that about $< 2\%$ of EEGs with a normal background are labeled as abnormal and $< 2\%$ of EEGs with an abnormal background are labeld as normal. These estimates are based on personal experience and reported inter-observer variability, see e.g. [1, 2].

Note, however, that a typical clinical EEG description does allow to include a measure for uncertainty in the conclusion of the EEG report, for instance phrases as "a nearly normal background pattern" or "slightly abnormal", are often used. This labeling was not possible by our approach. Future applications should include a measure for the (un-)certainty of the labels assigned.

Several aspects may contribute to the performance obtained. Firstly, we *assumed* that the labeling, as performed by the experts, was correct, and consistent. It is known, however, that human EEG interpretation may suffer from inconsistencies [1, 2]. Clearly, wrong labeling will yield suboptimal performance in the final classification. Secondly, we cannot exclude that non-explicit or even clinical knowledge is used in final description of the EEG (e.g. knowledge about the clinical condition of the patient). Also, artifacts may have been only (partially) removed in set 2; the sensitivity of the various features to

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artifacts has not been studied, thus far. Improvements can further be realized by various strategies, including artifact rejection, for instance by using ICA [15, 16], and perhaps additional or other features. Also, other classifiers can be considered. Preliminary results with the LESS classifier [17], show that LESS outperforms the Liknon and Lasso classifiers in the average sensitivity and specificity. Moreover, it uses substantially fewer features than both Liknon and Lasso. Furthermore, a larger data set may be needed, as well. The use of large databases for research and education has been increasingly recognized [18]. In the near future, we aim to realize data exchange between various hospitals in the Netherlands for educational and research purposes, such as the work described in this paper.

In conclusion, computer analysis of the EEG may assist in the interpretation, reveal so far unknown features of the EEG, and reduce inter-observer and intra-observer variability. However, several additional improvements are necessary to increase the sensitivity and specificity to values sufficient for clinical application.

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